Specular Reflection Removal in Smart Colposcopy Images Using Deep Learning Models for Enhanced Grading of Cervical Cancer

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By

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1. Introduction

Cervical cancer is a significant global health concern that predominantly affects women. This type of cancer originates in the cervix, the lower part of the uterus connecting to the vagina. It is caused by the uncontrolled growth of abnormal cells within the cervix, forming tumors. The primary factor contributing to the development of cervical cancer is the Human Papillomavirus (HPV), particularly certain persistent HPV infections. Other risk factors include smoking, a weakened immune system, long-term use of birth control pills, multiple sexual partners, and a family history of the disease. It ranked as the fourth most common cancer among women globally in 2020, according to the World Health Organization (WHO) [1]. An estimated 604,000 new cases are reported each year. This highlights the importance of awareness, prevention, and early detection efforts to combat this cancer. Approximately 90% of cervical cancer cases are reported highly in low- and middle-income countries, where access to crucial preventive measures is frequently constrained.

The cervical cancer impact is severe in this region, resulting in an estimated 342,000 annual fatalities. Various screening campaigns are organized using the clinical procedure, but due to its time consumption and invasive process, many women hesitate to use it. Clinical procedures like visual inspection, cervical biopsy, loop electrosurgical excision procedure, cone biopsy and HPV test are some campaign procedures for screening in the low-middle-income [2] [3]. Many women ignore this screening procedure due to its invasive and time-consuming procedure. So, to overcome these challenges, the mobileODT company introduced smart colposcopy to screen cervical cancer with the online management system incorporated with AI algorithms.

Smart colposcopy AI-based tools play a significant role in the campaign process of screening cervical cancer due to portability and robustness. It is an innovative medical technology that leverages artificial intelligence (AI) to enhance the screening and analysis of cervical cancer. This advanced tool is similar to digital colposcopy but incorporates AI algorithms to assist healthcare providers in interpreting cervical images. It leverages AI to provide real-time assistance to healthcare providers during the examination. The integration of AI can enhance the accuracy of cervical cancer screening by reducing the potential for human error in interpreting images. AI algorithms objectively assess cervical images, which can be particularly valuable in cases where multiple healthcare providers' interpretations may vary. It aids in the early detection of cervical abnormalities and lesions, allowing for timely intervention and prevention of the progression of cervical cancer [4].

Smart colposcopy employs a 13MP resolution camera with a working distance magnification of 250mm - 400mm, a 6000K 3W LED light and a wire grid polarizer for reflection reduction [6]. While this technology captures high-quality cervical images for diagnostic purposes, addressing image quality issues, particularly specular reflection artifacts, is a significant challenge. These artifacts appear as bright white pixels on some areas of cervix

images which are caused by the moisture content in the cervix tissue. Moisture absorbs light from the surrounding region, causing reflections that manifest as specular reflections on the digital images (Figure 1) [5]. Applying acetic acid to the cervix region induces color changes in abnormal lesion cells, turning them into acetowhite regions. While this aids in identifying abnormal lesions, the specular reflection can resemble acetowhite regions, posing difficulties for physicians in cancer detection and also cause the misdiagnosis during grading process. Despite efforts to refine image grading and segmentation models in smart colposcopy, more attention should be given to the crucial image quality issue. The presence of specular reflection artifacts in images presents diagnostic challenges, impacting the accuracy of the grading process. The technical challenge involves accurately identifying and removing reflection regions from smart colposcopy images. Existing approaches have shown limitations in achieving precise reflection identification and removal. In response, this discussion focuses on the methodology employed to enhance image quality by addressing and mitigating reflection regions.

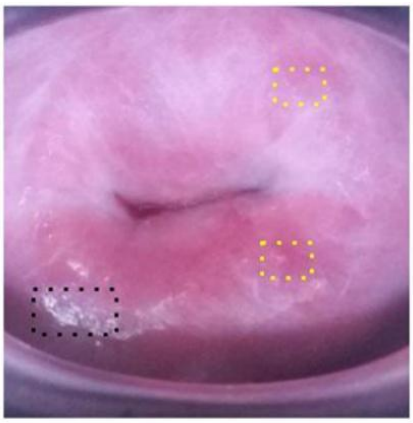

Figure. 1. Specular reflection on the cervix images (Black dotted box) captured through the smart colposcopy collected from the Kaggle dataset. The cervix's acetowhite region (yellow dotted box) resembles the specular reflection.

2. Problem Statement

Specular reflection, often observed as bright white regions within colposcopy images, poses a formidable challenge to the diagnostic process. These reflections can obscure critical areas of interest, particularly those associated with potential neoplasm growth. Physicians heavily rely on these images to identify and delineate regions of concern, and the presence of specular reflections introduces a significant source of ambiguity, making labeling neoplasm regions a complex and sometimes error-prone task. Smart colposcopy leverages artificial intelligence (AI) to aid in diagnosing and grading cervical cancer. The AI-based tools automate the grading and annotation of potential cancerous regions in the captured colposcopy images. However, the quality of the input images directly influences the accuracy and reliability of AI-based predictions. The grading quality is compromised when reflection regions caused by specular reflections are present in these images.

In some cases, these reflection regions closely resemble cancerous areas (i.e., acetowhite region), which can lead to misdiagnosis when interpreted by the AI algorithms. Understanding the nature and impact of specular reflections is essential to improving cervical cancer grading. Specular reflections occur when light is incident on a smooth, reflective surface at an angle equal to the angle of reflection. This phenomenon results in bright white areas appearing on the colposcopy images, masking critical details and introducing uncertainty into the diagnostic process. The proposed research seeks to develop advanced image processing techniques and algorithms specifically tailored to identify and remove specular reflections from colposcopy images.

Furthermore, this research endeavors to improve the integration of smart colposcopy images into AI-based diagnostic systems. It involves the development of robust image preprocessing methods that can effectively handle reflection regions. Enhancing the quality of input images can significantly reduce the likelihood of misdiagnoses and improve the overall performance of AI algorithms tasked with cancer grading. The expected outcomes of this research are twofold. First, it aims to provide medical practitioners with enhanced colposcopy images that are free from the interference of specular reflections. This improvement will lead to more accurate diagnoses, potentially identifying cervical cancer at earlier stages when treatment is most effective. Secondly, by elevating the quality of smart colposcopy images, there is a direct improvement in the precision and accuracy of the grading process, providing more reliable and detailed diagnostic information for healthcare professionals.

In conclusion, the research problem pertains to enhancing smart colposcopy images for improved cervical cancer diagnosis. The presence of specular reflections and reflection regions within these images poses significant challenges to medical practitioners and AI-based diagnostic systems. Addressing this problem is crucial to advancing cervical cancer diagnostics, ultimately leading to better patient care and outcomes. By developing specialized image processing techniques and improved integration with AI tools, this research endeavors to mitigate the impact of specular reflections and enhance the overall quality of cervical cancer diagnosis.

3. Research Objective

From the problem statement, the objective of the research work is given below:

Primary Objective

- The Primary Objective of the research is to detect and remove the specular reflection region from the smart colposcopy images to improve the grading process of cervical cancer.

Secondary objective:

The secondary objective of the research work is discussed below:

- Proposed an intensity-based threshold method to identify the specular reflection region on the smart colposcopy images.
- Proposed a deep learning inpainting model for filling the removed reflection region with the neighboring pixel on the smart colposcopy images.

4. Methodology

Specular reflection is the artefacts that have been ignored during medical image analysis. The research methodology proposes various techniques to analyze the optimized solutions to meet the research objectives. The deep learning algorithm and medical image processing techniques are used to meet the desired objectives. The methodology adopted for the proposed research work will be presented in four phases, as listed below:

Phase I: Specular Reflection Identification

Phase II: Segmentation of Reflection Region

Phase III: Deep Learning Inpainting Model

Phase IV: Grading of Smart Colposcopy Images

The solution proposed in this research work is efficient and viable for enhancing the quality of smart colposcopy images. The research design process in each chapter is visually represented in Figure 2.

4.1. Specular Reflection Identification

The main objective of this phase is to identify the reflection regions within smart colposcopy images. To accomplish this, a thorough investigation is conducted into various color spaces to determine which is best suited for identifying reflection regions. Once the optimal color space is identified, a threshold technique is employed to precisely delineate and locate the reflection region within the smart colposcopy images. The two main steps in identifying specular reflection are identifying suitable color space and the intensity-based threshold method.

4.1.1. Identification of Suitable Color Space

Each color space consists of channels with distinct characteristics, some of which closely correspond to the features of specular reflection. These unique properties in specific color space channels are valuable when identifying and isolating specular regions in medical images. According to the findings in the literature, the most commonly employed color spaces for

detecting specular reflections in digitized medical images are RGB, HSV, YUV, Lab, and XYZ[7][8][9]. In the context of smart colposcopy, images are initially converted into each color space, and visual analysis is then applied to these converted images. The color of the images becomes particularly important in subsequent analysis stages because detecting and removing reflections are part of the preprocessing steps. It's crucial that this preprocessing doesn't alter the color of the images. Based on our analysis, RGB and XYZ color spaces are better suited for smart colposcopy images because they align more closely with human visual perception.

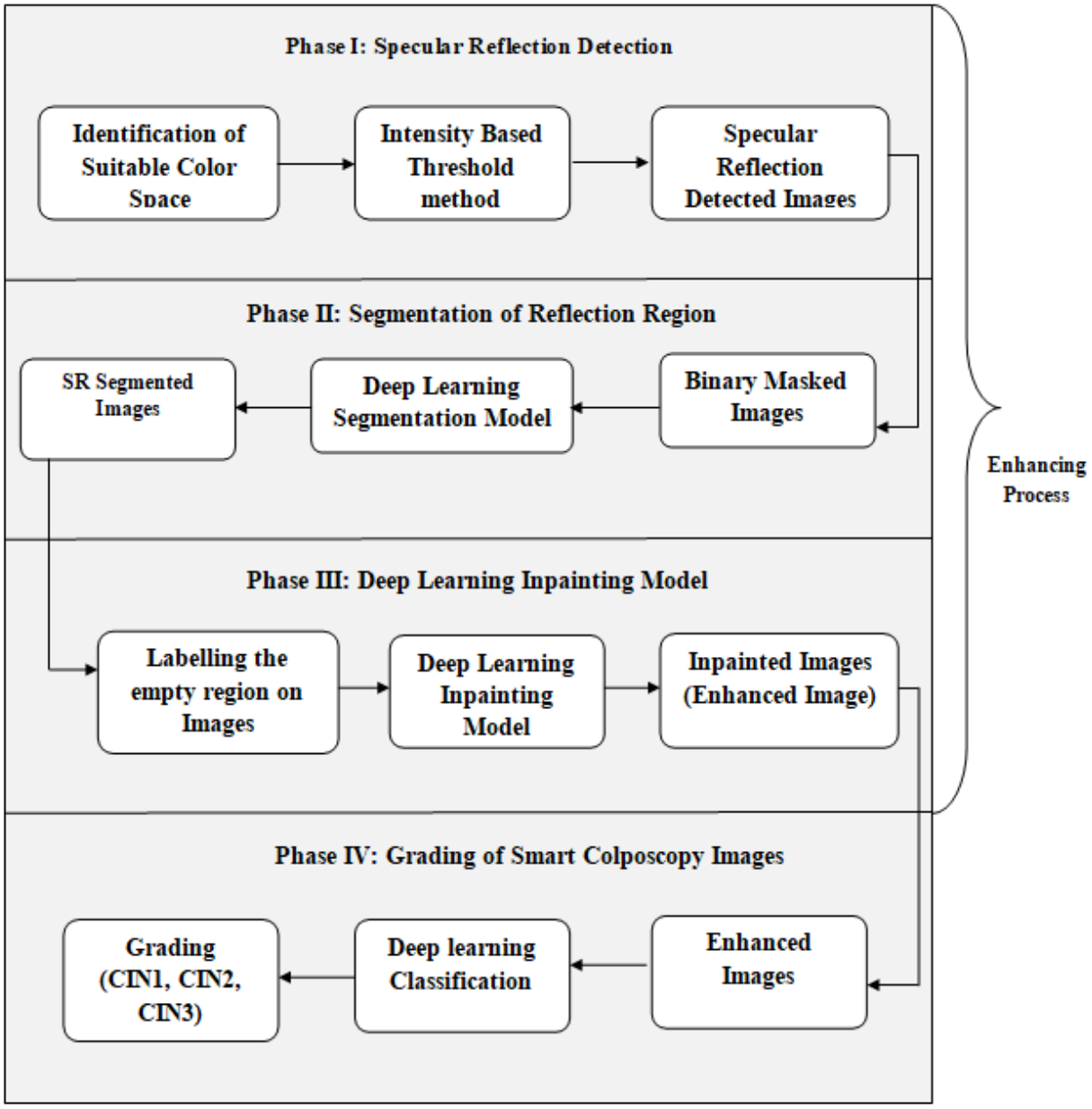
Phase I: Specular Reflection Detection
Identification of Suitable Color Space
Intensity Based Threshold method
Specular Reflection Detected Images
Phase II: Segmentation of Reflection Region
SR Segmented Images
Deep Learning Segmentation Model
Binary Masked Images
Phase III: Deep Learning Inpainting Model
Labelling the empty region on Images
Deep Learning Inpainting Model
Inpainted Images (Enhanced Image)
Phase IV: Grading of Smart Colposcopy Images
Grading (CIN1, CIN2, CIN3)
Deep learning Classification
Enhanced Images
Enhancing Process

Figure 2 Research Methodology

4.1.2. Proposed Approach using the Intensity-Based Threshold Method for specular reflection identification

After identifying the optimal color space, the threshold technique is employed on the RGB and XYZ color space images to precisely locate the reflection region on the smart colposcopy images**.** To apply the intensity-based threshold method, the bicubic interpolation method is initially applied to the images to resize the image of 256x256. It utilizes these nearby pixel values to create a bicubic polynomial interpolation function, which is then employed to calculate the pixel value at the desired output position. This technique aids in achieving more precise image resizing and enhancement. In an RGB color image, each channel is split into Red, Green and Blue channels, and the intensity value is calculated to find the average intensity value of the images. The digital images typically possess intensity values ranging from 0 to 255, where 0 corresponds to the darkest portions of the image, and 255 corresponds to the lightest areas. In the case of the RGB color space, the average intensity values typically fall within the range of 152 to 168.

Consequently, the manual analysis of intensity values for images in the RGB color space commences from a threshold of 150. Each intensity value range is manually analyzed to predict the reflection region on the smart colposcopy images. Based on the analysis, the intensity value ranges from 190-255 falls in the reflection region and the remaining region falls in the nonspecular reflection region on smart colposcopy images.

Similarly, in an XYZ color image, each channel is split into X, Y, and Z channels and the intensity value are calculated to find the average intensity value of the images. Similarly, the average intensity values typically range from 160 to 179 for the XYZ color space. Hence, the manual analysis of intensity values for images in the XYZ color space begins with a threshold of 160. Based on the analysis of each intensity value of the XYZ color space, the intensity value ranges from 201-255, precisely identifying the reflection region on the smart colposcopy images.

In summary, this research approach leverages bicubic interpolation and intensity analysis -across color channels to effectively detect reflection regions in smart colposcopy images, enhancing the quality of cervical image analysis. The experimental result is compared with the existing method, which is worked with the reflection detection process using different color spaces like RGB, HSV, XYZ and the fusion of many color spaces. Based on the comparison analysis, the proposed approach using the intensity-based threshold method on the XYZ color space identifies the reflection region on the smart colposcopy images with a higher accuracy.

4.2 Deep Learning Segmentation model

The reflections identified are labeled using the previous method to automate the identification process. Deep learning segmentation models help extract and acquire intricate features, leading to a more precise and resilient segmentation procedure. Convolutional neural network-based segmentation models are used for the segmentation of reflection from the smart

colposcopy images in this phase. The CNN-based segmentation model excels at performing pixel-level segmentation by utilizing masked images [10][11][12]. So, in this phase, the following steps involve binary masking and applying a deep learning segmentation model to segment the reflection region on the smart colposcopy images.

4.2.1. Proposed Binary Masking

In the previous stage, a threshold-based method relying on intensity marks the regions with reflections within the images. The result of this threshold operation is then converted into binary masks. In these binary masks, the areas with reflections are represented as white regions, indicated by the value 1, while the areas without specular reflections are depicted as black regions, represented by the value 0. This binary masking technique distinguishes and labels the regions with reflections and those without in the colposcopy images. During deep learning segmentation models' training process, the original images and their corresponding binary masks are utilized as inputs. This training setup allows the model to acquire the ability to identify and distinguish reflection regions, with the binary masks serving as reference labels for guidance.

4.2.2. Segmentation of reflection region on smart colposcopy images

Initially, highly used deep learning segmentation models like fully convolutional network (FCN), SegNet, and U-Net models are used for the segmentation of the specular reflection on smart colposcopy images[11][12][13]. These segmentation models are widely utilized in the medical image segmentation field, and among them, the U-Net model demonstrated superior performance due to its high segmentation accuracy even when provided with a limited dataset. The U-Net architecture is particularly well-suited for scenarios where dataset sizes are constrained. Since there are different versions of the U-Net model such as U-Net++ and Residual U-Net++ are systematically compared to determine the most suitable U-Net variant for effectively segmenting reflection regions within smart colposcopy images [14] [15]. The U-Net++ model exhibited the highest accuracy in predicting reflection regions on comparison analysis. To further enhance the model's performance in segmenting specular reflections in smart colposcopy images, the UNet model is fine-tuned. This fine-tuning process was designed to tailor the model specifically to the task of reflection region segmentation in smart colposcopy images. The overall process for segmenting smart colposcopy images using these deep learning models provides an overview of the methodology employed to achieve accurate and reliable specular reflection segmentation. The experimental result indicates the UNet model segments the reflection with a higher accuracy.

Consequently, various variations of the UNet model are employed to assess their performance in segmenting images. This UNet ++ predict higher, so the UNet++ model is

finetuned to reduce the over-segmentation process. The finetuned UNet++ model segments the reflection region with a higher accuracy.

4.3. Deep Learning Inpainting Model

Image inpainting is pivotal in computer vision and finding applications across various research domains. This technique proves invaluable in scenarios involving restoring damaged images, removing unwanted objects, and filling in missing regions within an image by extrapolating information from the surrounding pixels [16]. The inpainting method uses contextual information in the vicinity and harnesses the inherent structures, patterns, and textures present in the image to generate plausible and visually coherent completions for the missing portions. Initially, the inpainting method employs various filtering methods with multiple iterations to identify and delineate the missing regions within the images. However, as the methodology evolved, the machine learning algorithms and advanced techniques enhanced the quality of the reconstructed images, aiming for results that are not only realistic but also visually appealing. Through comprehensive analysis, it is determined that both bilateral filters and convolutional filters play pivotal roles in the inpainting process. However, in recent times, deep learning inpainting models have gained prominence, particularly those utilizing Convolutional Neural Networks (CNNs). These CNN-based models incorporate a sequence of convolutional filters to predict and reconstruct missing image regions. In conducting a comparative analysis, the bilateral filters generate missing information with higher quality when compared to convolutional filters. This superior performance can be attributed to the unique characteristics of bilateral filters. Unlike traditional convolutional filters, bilateral filters consider spatial and intensity weights assigned to each neighboring pixel and its corresponding intensity value. It achieves this by performing a weighted average of neighboring pixel values to compute the output pixel value. The bilateral filter considers the spatial distance between pixels in the image and the disparity in their intensity values. This dual consideration enables the bilateral filter to excel at preserving image edges and fine details while effectively reducing noise in the image. To further enhance this approach, it has integrated the intensity value component of the convolutional filter and supplemented it with the spatial weight from the bilateral filter. This proposed hybrid filter essentially replaces the traditional convolutional filter in the inpainting process. For training purposes, this novel filter was incorporated into the UNet model. This integration has led to developing the Bilateral-based Convolutional Inpainting model, specifically designed to predict and reconstruct missing regions within images. This model leverages the strengths of both the convolutional and bilateral filters to achieve superior inpainting results. The proposed method is not limited to smart colposcopy. The proposed model is applied to the different medical images and other digital images to check the model's performance. It is also tested with a higher masking ratio. The model fails when the masking ratio of the images is higher than 30%. An ablation study was conducted on the proposed model using different loss functions to solve the issues. The loss functions used in this study are pixel loss, perceptual loss, Total variation loss and style loss. Based on applying the loss function on

the masked images, the proposed method and the pixel loss function predict the large mask, i.e., 34-50 % with higher quality.

4.4. Grading smart Colposcopy images

The grading of smart colposcopy images refers to evaluating and categorizing the visual appearance of cervical abnormalities observed in the smart colposcopy images. One commonly used grading system is the cervical intraepithelial neoplasm (CIN) classification, which categorizes abnormal cell changes into different grades based on severity. The CIN system typically includes grades CIN1, CIN2, and CIN3, with CIN3 being the most severe and potentially indicating the presence of precancerous or cancerous cells. In grading smart colposcopy images, specular reflection can pose a significant challenge, potentially leading to inaccurate grading results. To mitigate this issue, enhanced images are utilized, which involve the critical step of detecting and removing reflection regions. Deep learning classification models, such as DenseNet121, VGG19, and EfficientNet, are highly effective for grading smart colposcopy images [17]. DenseNet121 is a convolutional neural network (CNN) architecture introduced by Huang in the year 2016. It belongs to the DenseNet family of models, which have gained widespread use in various computer vision tasks, including image classification, object detection, and segmentation. VGG19, on the other hand, is a CNN architecture developed by Simonyan and Zisserman in the year 2014. It is part of the VGG family of models and has been extensively employed in image classification tasks. VGG19 is characterized by its architecture, which consists of 19 layers, comprising 16 convolutional layers and three fully connected layers. EfficientNet is a CNN architecture introduced by Tan in the year 2019. It is renowned for its efficiency and robust performance across various computer vision tasks, particularly image classification. EfficientNet balances model size, computational efficiency, and accuracy by incorporating several innovative techniques. These deep learning models are robust tools for effectively grading smart colposcopy images, mainly when the enhanced images have addressed and removed reflection regions. A clear justification is needed to underscore the importance of specular reflection removal in improving the grading process of smart colposcopy images. The initial grading of non-enhanced images is conducted using a deep-learning classification model. Subsequently, the same deep-learning classification model is employed to grade the enhanced images. Based on the analysis, it becomes evident that the prediction accuracy significantly improves when working with the enhanced images. The deep learning classification model achieves a higher accuracy rate of 97.32% when classifying smart colposcopy images that have undergone specular reflection removal.

5. Contribution of the Research Work

The research contributes significantly to identifying and removing specular reflection in smart colposcopy images to enhance the grading of cervical cancer. The research contribution of each phase of research work is discussed in this session.

Phase I

The research contributes significantly to identifying specular reflection in smart colposcopy images. In this phase, conduct a thorough analysis of various color spaces to determine the most suitable one for identifying specular reflections in smart colposcopy images. The RGB and XYZ methods are ideal choices, particularly considering the screening procedure relies on the naked eye, necessitating the retention of color originality. The study employs an intensity-based threshold method on smart colposcopy images to effectively identify the reflection region associated with specular reflections. This method enhances the accuracy of detection by focusing on intensity variations. The research conducts a comparison analysis of specular reflection detection across different color spaces. The proposed RGB and XYZ methods stand out in accurately identifying specular reflections, with the qualitative analysis highlighting the superior accuracy of the XYZ method. The proposed XYZ method accurately identifies specular reflections in smart colposcopy images. The qualitative analysis emphasizes the method's effectiveness in maintaining the color of the images, which is crucial for accurate interpretation by medical professionals. The study identifies a limitation in the RGB method, specifically its failure to preserve color appearance during the reflection process. This limitation underscores the importance of choosing the right color space for specular reflection identification in medical imaging. The significance of the research extends beyond smart colposcopy images. The performance of the proposed method is validated and found to be effective in identifying reflection regions in smart colposcopy and other medical images such as digital colposcopy, endoscopy, and colonoscopy images. This broadens the potential applications of the proposed method in diverse medical imaging scenarios. The research provides a robust and accurate method for identifying specular reflections in smart colposcopy images, with implications for various medical imaging modalities. The emphasis on color accuracy and extending the proposed method's applicability to different medical images enhance its contribution to medical image analysis and interpretation.

Phase II

The research significantly contributes to computer vision, specifically in the context of smart colposcopy image segmentation for specular reflection identification. The research introduces and employs a finetuned UNet++ deep learning segmentation model for precisely identifying and segmenting specular reflection regions in smart colposcopy images. The UNet++ architecture is chosen for its ability to capture intricate features, leading to enhanced segmentation accuracy. The finetuning process tailors the model specifically for the task of reflection region segmentation, optimizing its performance in the context of cervical cancer diagnosis. The research conducts a thorough comparative analysis of widely used segmentation models, including fully convolutional network (FCN), SegNet, and U-Net. The U-Net model demonstrates superior performance, particularly in scenarios with limited datasets. The systematic comparison also evaluates different versions of the U-Net model,

with the research identifying U-Net++ as the most suitable variant for effectively segmenting reflection regions within smart colposcopy images. This comparative analysis contributes valuable insights for researchers and practitioners in choosing optimal segmentation models for similar applications. The research introduces a fine-tuning process designed explicitly for the UNet++ model to enhance further the model's performance in segmenting specular reflections. This fine-tuning tailors the model to the intricacies of reflection region segmentation, ensuring optimal performance. The fine-tuned UNet++ model exhibits the highest accuracy in predicting reflection regions, showcasing the effectiveness of this approach in improving segmentation outcomes.

In summary, the research contributes novel methodologies, addresses challenges in data scarcity, conducts a comparative analysis of segmentation models, introduces a finetuned UNet++ model, and provides a comprehensive methodology overview. These contributions collectively advance the capabilities of deep learning segmentation models for precisely identifying specular reflections in smart colposcopy images, with direct implications for improving cervical cancer diagnosis.

Phase III

The research introduces a novel bilateral convolutional inpainting model with impressive capabilities in removing reflection regions from smart colposcopy and other medical images. The proposed model demonstrates effectiveness in removing reflection regions from smart colposcopy images. It achieves this by seamlessly filling the removed regions with high-quality pixels, resulting in improved image quality suitable for medical analysis and diagnosis. The research extends the application of the proposed inpainting method to diverse datasets, including Place 2, the Open Logo dataset, and satellite images. The model performs well across these datasets, showcasing its versatility in removing specified objects and filling regions with neighboring high-quality pixels. This suggests broad applicability in various domains beyond medical imaging. To ensure the robustness of the inpainting method, the proposed model undergoes testing with different masking ratios. The results indicate exceptional performance, particularly in predicting missing pixel values for the largest masked areas. This highlights the model's ability to handle substantial inpainting tasks and outperform other deep learning inpainting methods. The research explores the impact of different loss functions on inpainting quality, particularly in more significant masked regions. The combination of total variation loss and pixel loss with the proposed method leads to better predictions of missing pixel values in larger masked areas, enhancing the overall inpainting quality. The proposed bilateral convolutional inpainting model is positioned as a valuable tool for image restoration tasks. Its success in removing reflection regions and desired objects and the ability to tailor loss functions for specific tasks suggests its potential to enhance image quality in various applications. The research underscores the model's potential significance in medical imaging, particularly smart

colposcopy images. Additionally, its application to satellite imagery highlights its broader utility in diverse fields where object removal and inpainting are crucial.

In summary, the research introduces a versatile and effective bilateral convolutional inpainting model with applications in reflection removal from medical images and object removal from various datasets. The findings emphasize its potential impact on image restoration tasks, with implications for medical imaging and other domains requiring high-quality inpainting results.

Phase IV

The research comprehensively evaluated three deep-learning models (Efficient, VGG19, and DenseNet121) for grading smart colposcopy images, focusing on applying an enhancement technique. Using the proposed enhancement technique led to remarkable improvements in the accuracy of all three models. Specifically, the enhanced Efficient model achieved an accuracy of 91.79%, the enhanced VGG19 model achieved 96.32%, and the improved DenseNet121 model achieved an impressive accuracy of 97.32%, all at the epoch value of 60. These results underscore the enhancement technique's substantial impact on the models' grading performance. Visual representations of the enhanced images played a crucial role in validating the improved performance of the models.

The visualizations showcased the quality of the enhanced images and how they contributed to more accurate and reliable predictions for cervical cancer grading. This visual evidence strengthens the research's findings and provides insights into the enhanced models' ability to interpret and classify images. The associated loss values served as a quantitative measure of the effectiveness of the models' training process with improved images. The minimized differences between predicted and actual labels, as reflected in the loss values, demonstrate the success of the enhancement technique in guiding the models towards more accurate predictions. This aspect further supports the overall improved performance of the enhanced models. The research includes a comparative analysis by evaluating the models without any enhancement. The baseline accuracies of 93.27%, 95.02%, and 92.72% for the Efficient, VGG19, and DenseNet121 models, respectively, highlight the need for improvement. The subsequent application of the enhancement technique significantly elevates the grading performances, emphasizing the technique's potential for enhancing medical image analysis. The research findings directly affect cervical cancer grading using smart colposcopy images. The improved accuracy of the models suggests the practical application of the proposed enhancement technique in clinical settings, where accurate grading is crucial for effective diagnosis and treatment planning.

In summary, the research not only showcases the effectiveness of the proposed enhancement technique in improving the accuracy of deep-learning models but also emphasizes its potential clinical relevance in the context of cervical cancer grading. Integrating visual representations and loss values strengthens the research's contributions, providing a

comprehensive understanding of the enhanced models' performance in smart colposcopy image analysis.

6. **Conclusion**

In conclusion, the research employs a comprehensive methodology for addressing specular reflections in smart colposcopy images, focusing on enhancing cervical image analysis. The specular reflection detection phase involves meticulously exploring color spaces, with RGB and XYZ identified as optimal choices. The proposed intensity-based threshold method, applied after bicubic interpolation, demonstrates precision in locating reflection regions. The deep learning segmentation model utilizes binary masking and fine-tuned U-Net++ to segment specular reflections accurately. Introducing a Bilateral-based Convolutional Inpainting model further contributes to image reconstruction, integrating bilateral and convolutional filters for superior inpainting results. While tested on various medical and digital images, the model faces limitations with higher masking ratios, prompting an ablation study using different loss functions to improve performance. In the grading phase, the research emphasizes the challenge posed by specular reflections in inaccuracies and introduces enhanced images through reflection region removal. Deep learning classification models, including DenseNet121, VGG19, and EfficientNet, prove effective for grading smart colposcopy images. The study underscores the significance of specular reflection removal in achieving a remarkable accuracy rate of 97.32% in classifying enhanced smart colposcopy images.

The research offers a holistic approach, combining advanced techniques in color space analysis, threshold methods, deep learning segmentation, inpainting, and classification for improved smart colposcopy image analysis and grading.

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8. Publications

Patent Publication

1. Subashini, P., Dhivyaprabha, T.T., **Jennyfer Susan, M.B**. Cervical Cancer Self-Test Kit , Application No.-202241021066,May 2022.

Book Publication

1. Subashini, P., Dhivyaprabha, T.T., **Jennyfer Susan, M.B**. (2023). Machine Learning Using Google Colab – for Chemistry and Biochemistry Applications, *Notion Press*. ISBN: 9798889239963.

Chapter Publications

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